REPORT DOCUMENTATION PAGE

Form Approved OMB NO. 0704-0188

1. REPORT DATE (DD-MM-YYYY)	2. REPORT TYPE	3. DATES COVERED (From - To)
	New Reprint	-

4. TITLE AND SUBTITLE

A distributed and energy-efficient framework for Neyman-Pearson detection of fluctuating signals in large-scale sensor networks

5a. CONTRACT NUMBER	W911NF-08-1-0449
5b. GRANT NUMBER	
5c. PROGRAM ELEMENT NUMBER	611102
5d. PROJECT NUMBER	
5e. TASK NUMBER	
5f. WORK UNIT NUMBER	

6. AUTHORS

Yang Yang, Rick Blum, Brian Sadler

7. PERFORMING ORGANIZATION NAMES AND ADDRESSES

Lehigh University
Office of Research & Sponsored Programs
Lehigh University
Bethlehem, PA 18015 -

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

U.S. Army Research Office
P.O. Box 12211
Research Triangle Park, NC 27709-2211

10. SPONSOR/MONITOR'S ACRONYM(S)
ARO

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
54261-NS.33

12. DISTRIBUTION AVAILIBILITY STATEMENT

Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

The views, opinions and/or findings contained in this report are those of the author(s) and should not contrued as an official Department of the Army position, policy or decision, unless so designated by other documentation.

14. ABSTRACT

To address the challenges inherent to a problem of practical interest — of Neyman-Pearson detection of fluctuating radar signals using wireless sensor networks, we propose in this paper a distributed and energy-efficient framework. Such framework is scalable with respect to the network size, and is able to greatly reduce the dependence on the central fusion center. It assumes a clustering infrastructure, and addresses signal processing and communications related issues arising from different layers. This framework includes a distributed scheduling

15. SUBJECT TERMS

Distributed routing, distributed scheduling,Kullback-Leibler distance, Neyman-Pearson criterion, signal detection,and wireless sensor networks.

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	15. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Rick Blum
UU	UU	UU	UU		19b. TELEPHONE NUMBER: 610-758-3459

Report Title

A distributed and energy-efficient framework for Neyman-Pearson detection of fluctuating signals in large-scale sensor networks

ABSTRACT

To address the challenges inherent to a problem of practical interest — of Neyman-Pearson detection of fluctuating radar signals using wireless sensor networks, we propose in this paper a distributed and energy-efficient framework. Such framework is scalable with respect to the network size, and is able to greatly reduce the dependence on the central fusion center. It assumes a clustering infrastructure, and addresses signal processing and communications related issues arising from different layers. This framework includes a distributed scheduling protocol and a distributed routing protocol, which enable sensor nodes to make their own decisions about information transmissions, without requiring the knowledge of the network global information. In this framework, energy efficiency manifests itself at different network layers in a distributed fashion, and a balance between the detection performance and the energy efficiency is also attained.

REPORT DOCUMENTATION PAGE (SF298)
(Continuation Sheet)

Continuation for Block 13

ARO Report Number 54261.33-NS
A distributed and energy-efficient framework for ...

Block 13: Supplementary Note

Approved for public release; distribution is unlimited.

A Distributed and Energy-Efficient Framework for Neyman-Pearson Detection of Fluctuating Signals in Large-Scale Sensor Networks

Yang Yang, *Member, IEEE*, Rick S. Blum, *Fellow, IEEE*, and Brian M. Sadler, *Fellow, IEEE*

***Abstract*—To address the challenges inherent to a problem of practical interest — of Neyman-Pearson detection of fluctuating radar signals using wireless sensor networks, we propose in this paper a distributed and energy-efficient framework. Such framework is scalable with respect to the network size, and is able to greatly reduce the dependence on the central fusion center. It assumes a clustering infrastructure, and addresses signal processing and communications related issues arising from different layers. This framework includes a distributed scheduling protocol and a distributed routing protocol, which enable sensor nodes to make their own decisions about information transmissions, without requiring the knowledge of the network global information. In this framework, energy efficiency manifests itself at different network layers in a distributed fashion, and a balance between the detection performance and the energy efficiency is also attained.**

***Index Terms*—Distributed routing, distributed scheduling, Kullback-Leibler distance, Neyman-Pearson criterion, signal detection, and wireless sensor networks.**

I. Introduction

FOR A GOOD many envisioned applications of wireless sensor networks (WSNs), signal detection based on data collected from distributed sensors often serves as the initial step, taken prior to any other processing, and has been intensely studied over the years. Considering a scenario of using networked radar-like sensors to detect the possible presence of an illuminated target at a specific geographical location, our previous work [1], [2] addressed the problem of energy-efficient routing for signal detection under the Neyman-Pearson criterion. We assumed a powerful fusion center which has the knowledge of the geographical location of each sensor, determines the location to be probed, and more importantly, jointly optimizes detection and routing in a centralized manner by precomputing the routes as a function of the geographical location to be monitored. However, as the size of a sensor network grows large, which is likely to happen due to sensors' low cost and small size as well as their ease for deployment, it may appear demanding if such premise of a very powerful central unit continues to be employed. Thus for this problem of practical interest, it is desirable to develop appropriate schemes which are scalable and able to reduce the stringent requirement on the processing capability of the fusion center. These schemes, in the meantime, should optimize the detection performance of the system, and should address as well the inherent design challenges of WSNs, including their dependence on finite battery energy.

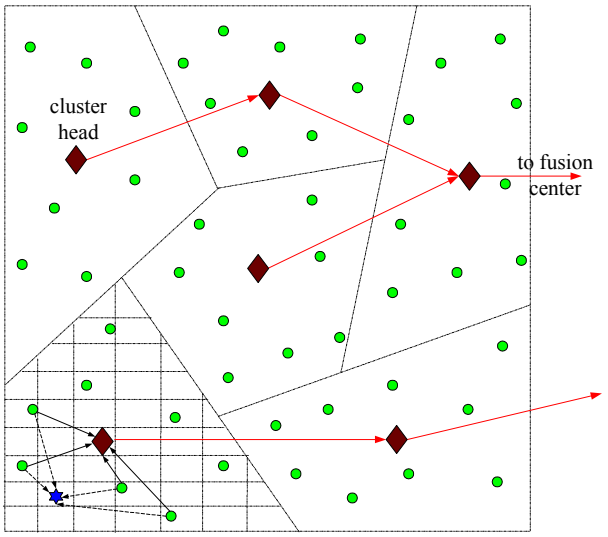


Fig. 1: System architecture of a large-scale wireless sensor network for detecting scattering signals. The 6-sided star represents the scattering source to be detected.

In this paper, our focus lies in determining the presence of fluctuating targets using distributed radar-like sensors. Motivated to address the above-mentioned challenges and to obtain a useful and practically viable wireless sensor networking solution, we propose a novel distributed and energy-efficient framework for the problem of signal detection in large-scale WSNs through active sensing, which to the best of our knowledge, is not available in the literature. This framework is based on a clustering infrastructure. In other words, the network is divided into small clusters, and each cluster will elect a cluster head. This is illustrated in Fig. 1 where inter-cluster communications are performed among the cluster head nodes using multi-hop routing, while intra-cluster communications are normally between nodes residing inside the cluster and the cluster head. The signal detection task is carried out by the non-cluster head nodes inside each cluster. Each cluster head, acting as a local control center, will make a binary decision

Manuscript received 30 April 2009; revised 12 February 2010. This material is based on research supported by the Air Force Research Laboratory under agreement FA9550-09-1-0576, by the National Science Foundation under Grant CCF-0829958, and by the U.S. Army Research Office under Grant W911NF-08-1-0449.

Y. Yang and R. S. Blum are with the Department of Electrical and Computer Engineering, Lehigh University, 19 Memorial Drive West, Bethlehem, PA 18015, USA (e-mail: yay204@lehigh.edu; rblum@ece.lehigh.edu).

B. M. Sadler is with the Army Research Laboratory, Adelphi, MD 20783 USA (e-mail:bsadler@arl.army.mil).

Digital Object Identifier 10.1109/JSAC.2010.100919.

about the presence of a target at a specified location given the information it collects, and will report to the fusion center via multi-hop routing only when the hypothesis test is true. This reduces the data set that needs to be transmitted to the fusion center, and thus alleviates the storage and processing requirement on the fusion center.

The system design involves several intertwined network layers, including the physical layer, the media access control (MAC) layer, and the routing layer. In fact, apart from modeling this application-specific sensor network, a major contribution of our work is that it provides and integrates distributed solutions targeted at different layers. Moreover, through exploiting a tight coupling between the physical and the upper layers (the MAC layer in particular), our framework can attain appealing tradeoffs between the energy efficiency and the detection reliability. The contributions of this paper are summarized as follows:

- Related to the physical layer is a distributed signal processing scheme that includes a thorough analysis of the Neyman-Pearson detection of fluctuating narrowband radar signals from distributed sensors, and a proposal of a channel-capacity-like detection performance metric based on the Kullback-Leibler distance.
- By exploiting the statistical and instantaneous information obtained via in-network processing, we propose a new scheduling protocol which allows each non-cluster head node to make an autonomous decision about when to transmit, and strikes a balance between the detection performance and the energy savings.
- To regulate the inter-cluster communications, we present a distributed routing scheme which allows each cluster head to construct its own routing decisions with its available information, and from consultation with immediate neighbors, to minimize the overall energy cost for information transmission to the fusion center.

The remainder of this paper is organized as follows. In Section II, we introduce the system architecture and the signal model. In Section III, we focus on the Neyman-Pearson detection of fluctuating radar signals, and propose to use the Kullback-Leibler distance as the performance metric. In Section IV, we focus on the distributed scheduling design, and propose a simple scheduling protocol and its distributed implementation. In Section V, we study the multi-hop routing among cluster heads, and present a distributed routing algorithm. Simulation examples are given in Section VI. Finally, Section VII concludes this paper.

II. System and Signal Model

A. System Architecture

We consider a sensor network which consists of a large amount of sensors that are distributed over a geographical field, and a fusion center which can be inside or outside the field. For simplicity we assume the clusters are formed and do not change dynamically, while noting that the cluster head role can rotate among nodes to ensure energy fairness. Those clusters can be formed in several different ways, one of which, for example, is the low-energy adaptive clustering hierarchy in [3]. The specific geographical area covered by each cluster which is relatively small in size, is further divided into multiple range resolution cells[1] (cf. Fig. 1). Each range resolution cell is probed sequentially by sensors inside a cluster, using radar pulses and according to some desired schedule.

We assume each cluster head has the following knowledge: the locations of its immediate neighbors in the routing, the range resolution cells which compose the area covered by its cluster, and the members which belong to the cluster as well as each member's physical location. It, however, does not know the energy level of each sensor inside the cluster. For each non-cluster head node, we assume it knows its own location and the location of its cluster head. It also knows the order of cell probing as well as the location of each specific cell to probe. However, it does not have the knowledge of the location and energy level of each of its neighbors. Thus, cooperation for information transfer to the cluster head is not pursued here, although it could be incorporated into our framework. We also assume that the energy consumed for sensing is in general, relatively small as compared to that dissipated in data communication.

B. Signal Model

Suppose sensor i is chosen to perform the sensing task according to a certain criterion, e.g., if its residual energy is beyond a certain level and its distance to the target location is within a certain range. Then the illuminating signal sent from sensor i can be expressed as

$$s_i(t) = f_i(t)\sin[w_i t + \phi_i] \tag{1}$$

where w_i denotes the carrier frequency, $f_i(t)$ corresponds to the signal envelope, and ϕ_i corresponds to a phase angle. We assume the transmitted signals are both amplitude- and phase-modulated, but w_i varies from sensor to sensor to reduce the signal interference. We model the target as a point scatterer, so the reflected waveform will be an attenuated and varied version of the transmitted waveform. We consider the situation that both the amplitude and phase of the received signal vary. This happens when the target's aspect or effective radar cross section changes from pulse to pulse. In the communication context, this situation is usually referred to as fading. We assume echo signals arrive at each sensor node with independent fading. Under H_1 (target present), we model the received signal as

$$r_i(t) = v_i f_i(t-\tau_i)\sin[w_i(t-\tau_i) + \phi_i + \theta_i] + n_i(t) \tag{2}$$

where τ_i is the delay, $n_i(t)$ denotes the independently and identically distributed Gaussian noise with variance $\sigma_{n_i}^2$. v_i and θ_i are independent random variables which correspond to the amplitude variation and phase noise, respectively. We assume v_i has a Rayleigh density with parameter $\sigma_{v_i}^2$ as follows

$$\zeta(v_i) = \begin{cases} \frac{v_i}{\sigma_{v_i}^2}\exp\left\{-\frac{v_i^2}{2\sigma_{v_i}^2}\right\} & v_i > 0 \\ 0 & v_i \le 0 \end{cases}$$

[1]For the given sensor processing, it is statistically very unlikely to distinguish two or more targets that are located within the same range resolution cell [4].

We assume θ_i is uniformly distributed over $[0, 2\pi]$. For simplicity, (2) does not account for the clutter and Doppler effects that might also occur, although these can be incorporated in standard ways. Further, we also assume that the path loss attenuation effect is embedded in v_i (thus $\sigma_{v_i}^2$), so that we do not need to explicitly deal with the distance between the target and sensor i. In practice, we can use neighboring range cells to estimate the noise/clutter power, and the known distance traveled by the probing radar signals to estimate the relative propagation losses.

As the probe location is known to sensor i, there would be no difference if we simply let $\tau_i = 0$. Further, we consider sampled signals in the sequel for convenience. Let T_i be the sampling interval, and K be the number of samples available at sensor i. Then under hypotheses H_1 and H_0, the sampled waveform for $k = 1, \cdots, K$ can be written as

$$r_i(k) = \begin{cases} v_i f_i(k) \sin[(k-1)w_i T_i + \phi_i + \theta_i] + n_i(k), & H_1 \\ n_i(k), & H_0 \end{cases}$$

where $f_i(k) = f_i((k-1)T_i)$, $n_i(k) = n_i((k-1)T_i)$, $k = 1, \cdots, K$ are the sampled waveform $f_i(t)$, and noise $n_i(t)$, respectively.

III. Neyman-Pearson Detection of Fluctuating Radar Signals

A. The Neyman-Pearson Detector

By definition, the local likelihood ratio at sensor i is given by (3) at the bottom of this page, where $\overline{f_i^2} = (1/K)\sum_{k=1}^{K} f_i^2(k)$, L_i^c and L_i^s are respectively defined as

$$\begin{aligned} L_i^c &= \sum_{k=1}^{K} r_i(k) f_i(k) \cos[(k-1)w_i T_i + \phi_i], \\ L_i^s &= \sum_{k=1}^{K} r_i(k) f_i(k) \sin[(k-1)w_i T_i + \phi_i]. \end{aligned}$$

It does not appear straightforward to compute or simplify (3). But fortunately, it can be shown that L_i^s and L_i^c are sufficient statistics [5]. In fact, they are also jointly Gaussian under both hypotheses. For each sensor i, given H_0, L_i^c and L_i^s are independent Gaussian random variables and distributed according to $\mathcal{N}(0, \sigma_{0i}^2)$, where $\sigma_{0i}^2 = K\overline{f_i^2}\,\sigma_{n_i}^2/2$. Similarly, under H_1, L_i^c and L_i^s are also independent Gaussian random variables, but they are distributed according to $\mathcal{N}(0, \sigma_{1i}^2)$, where $\sigma_{1i}^2 = K\overline{f_i^2}\,\sigma_{n_i}^2/2 + (K\overline{f_i^2})^2\,\sigma_{v_i}^2/4$. Therefore, the log-likelihood ratio at each sensor i can be computed in terms of L_i^c and L_i^s, and can be written as

$$\Lambda_i = \ln \frac{p(L_i^c, L_i^s|H_1)}{p(L_i^c, L_i^s|H_0)} = \ln \sigma_{0i}^2 - \ln \sigma_{1i}^2 + \alpha_i^2[(L_i^c)^2 + (L_i^s)^2]$$

where $\alpha_i^2 = (\sigma_{0i}^{-2} - \sigma_{1i}^{-2})/2$.

We assume there are N sensors inside a cluster that perform the sensing task. Additionally, we will use the following conditional independence assumption throughout the paper: the observations of all sensors are statistically independent, conditioned on the binary hypothesis. Note that this assumption is very common in distributed detection problems. Thus L_i^c, L_i^s, $i = 1, \cdots, N$, are all independent distributed Gaussian variables under both hypotheses. Then, the overall log-likelihood ratio can be calculated through

$$\Lambda = \sum_{i=1}^{N} \Lambda_i = \sum_{i=1}^{N} (\ln \sigma_{0i}^2 - \ln \sigma_{1i}^2) + \sum_{i=1}^{N} \alpha_i^2[(L_i^c)^2 + (L_i^s)^2].$$

Incorporating the threshold η, the Neyman-Pearson test which according to the Neyman-Pearson lemma [5] is a likelihood ratio test, can be written as

$$\underbrace{\sum_{i=1}^{N} \alpha_i^2[(L_i^c)^2 + (L_i^s)^2]}_{l} \underset{H_0}{\overset{H_1}{\gtrless}} \underbrace{\eta - \sum_{i=1}^{N} (\ln \sigma_{0i}^2 - \ln \sigma_{1i}^2)}_{\eta'} \quad (4)$$

where we have defined the test statistic l and the new threshold η'. A detailed performance analysis of the above Neyman-Pearson detector can be found in [6, Appendix B], which indicates that obtaining a closed-form relation between the probability of detection P_D and the probability of false alarm P_F can be a rather formidable task. Further, such performance analysis unfortunately does not immediately render much insight into the design of the whole system. Therefore, next we propose to employ an alternative measure to characterize the detection performance of the Neyman-Pearson detector.

B. The Kullback-Leibler Distance

We consider the Kullback-Leibler distance [7] as an alternative performance index. The Kullback-Leibler distance is the expected value of the log-likelihood ratio taken over the density of one of the hypotheses. It is one of the most frequently used information-theoretic distance measures, and is related to the Neyman-Pearson detector's performance through Stein's lemma [8, p. 93]. We state this result in the following without proof:

Theorem 1 (Stein's Lemma): Consider a hypothesis test where we want to distinguish between the null probability density $p_0(y)$ and the alternative probability density $p_1(y)$. Suppose we have collected independent observations y_1, y_2, $\cdots$, y_N. Assume $D(p_0\|p_1) < \infty$, where $D(p_0\|p_1)$ denotes the Kullback-Leibler distance or the relative entropy of p_1 with respect to true distribution p_0, and is defined to be

$$D(p_0\|p_1) = \int p_0(y) \ln \frac{p_0(y)}{p_1(y)}\, \mathrm{d}y.$$

Let A_N be an acceptance region for hypothesis H_0, and A_N^c be the acceptance region for hypothesis H_1. Let $\beta_N = P_1^N(A_N)$ denote the miss error probability, i.e., Pr(choose $H_0|H_1$ is true) and $\alpha_N = P_0^N(A_N^c)$ denote the false alarm probability,

$$L_i = \exp\left\{-\frac{K\overline{f_i^2}}{4\sigma_{n_i}^2}\right\} \times \frac{1}{2\pi} \int_0^{2\pi} \int_0^{\infty} \zeta(v_i) \exp\left\{\frac{1}{\sigma_{n_i}^2}\,(L_i^c v_i \sin\theta_i + L_i^s v_i \cos\theta_i)\right\} \mathrm{d}v_i\, \mathrm{d}\theta_i \quad (3)$$

i.e., Pr(choose $H_1|H_0$ is true). For $0 < \epsilon < 1/2$, we define

$$\beta_N^\epsilon = \min_{\alpha_N < \epsilon} \beta_N.$$

Then

$$\lim_{\epsilon \to 0} \lim_{N \to \infty} \frac{1}{N} \ln \beta_N^\epsilon = -D(p_0 \| p_1). \qquad \square$$

Stein's lemma indicates that the Kullback-Leibler distance is the exponential rate at which the error probabilities decay for a Neyman-Pearson detector. This result is independent of the false alarm level (i.e., upper bound constraint on P_F) as long as such level is neither 0 nor 1 [8, p. 93]. The Kullback-Leibler distance is additive, i.e., the distance between two joint distributions of statistically independent distributed random variables is equal to the sum of the marginal distance [7, p.12]. Therefore, for the problem that we are interested in where all the Gaussian random variables, L_i^c, L_i^s, $i = 1, \cdots, N$ are independent, assuming sufficiently large N, the probability of miss is given by

$$P_M \approx g(N) \cdot \exp\left\{ -\sum_{i=1}^{N} D_i(p(L_i^c, L_i^s|H_0) \| p(L_i^c, L_i^s|H_1)) \right\} \tag{5}$$

where $g(N)$ is a positive-valued function that satisfies

$$\lim_{N \to \infty} \frac{1}{N} \ln g(N) = 0. \tag{6}$$

Eq. (6) states that the logarithm of $g(N)$ increases more slowly than a linear function. Because $g(N)$ changes slowly, the asymptotic variation of P_M with respect to N is captured by the exponential term, and thus by the sum of each individual Kullback-Leibler distance. For convenience, we use D to denote the sum term in (5), and use D_i for short for each term in the summation. Then, we have the following result:

Lemma 1: Define $\mathtt{snr}_i = K\overline{f_i^2}\sigma_{v_i}^2/2\sigma_{n_i}^2$ as the nominal signal-to-noise ratio at each sensor i. Then the Kullback-Leibler distance at each sensor i is given by:

$$D_i = \ln(1 + \mathtt{snr}_i) - \left(1 + \frac{1}{\mathtt{snr}_i}\right)^{-1}. \tag{7}$$

Proof: Based on the definition, we compute the Kullback-Leibler distance D_i as follows:

$$\begin{aligned} D_i &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} p(L_i^c, L_i^s|H_0) \ln \frac{p(L_i^c, L_i^s|H_0)}{p(L_i^c, L_i^s|H_1)} \mathrm{d}L_i^s \mathrm{d}L_i^c \\ &= \ln \sigma_{1i}^2 - \ln \sigma_{0i}^2 - \alpha_i^2 \mathrm{E}\{(L_i^c)^2 + (L_i^s)^2|H_0\} \\ &= \ln\left[1 + \frac{K\overline{f_i^2}\sigma_{v_i}^2}{2\sigma_{n_i}^2}\right] - \frac{K\overline{f_i^2}\sigma_{v_i}^2}{K\overline{f_i^2}\sigma_{v_i}^2 + 2\sigma_{n_i}^2}. \end{aligned}$$

Applying $\mathtt{snr}_i = K\overline{f_i^2}\sigma_{v_i}^2/2\sigma_{n_i}^2$, we obtain (7). ■

Note that $\mathtt{snr}_i$ is indeed related to the true signal-to-noise ratio, because the average energy of the received signal (excluding the noise) is given by

$$\mathrm{E}\left\{ \sum_{k=1}^{K} \left(v_i f_i(k) \sin[(k-1)w_i T_i + \phi_i + \theta_i] \right)^2 \right\} = K\overline{f_i^2}\sigma_{v_i}^2.$$

We present below some properties of D_i without proof.

Lemma 2: D_i has the following properties:

1) D_i is strictly positive.
2) D_i is strictly increasing with respect to $\mathtt{snr}_i$.
3) D_i is a strictly concave function of $\mathtt{snr}_i$ for $\mathtt{snr}_i > 1$.

Lemma 1 and *2*, along with *Theorem 1*, yield the following result:

Proposition 1: The contribution of each sensor i to the overall detection performance of the Neyman-Pearson detector is quantified by its Kullback-Leibler distance D_i.

Strictly speaking, the Kullback-Leibler distance only determines asymptotic performance. In other words, the relation between the Kullback-Leibler distance and P_M, as manifested in (5), does not directly lead to a numeric estimate of P_M. Nevertheless, the variation of P_M with respect to D (thus D_i) can be determined through (5) and with assurance that the accuracy of the predicted variation will improve as the number of independent observations, i.e., N, increases. Therefore, D_i lends itself to be an amenable measure to determining a sensor's importance in the Neyman-Pearson detection. The larger the value of D_i, the more important a sensor's observations for the test.

Remark 1: For relatively high $\mathtt{snr}_i$, (7) reduces to

$$D_i \approx \ln(1 + \mathtt{snr}_i) - 1. \tag{8}$$

The first term in (8) is well recognized[2], which in communications denotes the channel capacity of the complex Gaussian channel. For this specific problem of interest, it can be interpreted as the amount of information contained in the observations of sensor i, or the uncertainty that is reduced about the target presence through collecting information from sensor i. The second term is a constant and is the same for each different sensor under high $\mathtt{snr}_i$.

IV. Distributed Scheduling Design

A. Problem Statement

After probing a specific resolution cell and capturing the echo signal, the non-cluster head node which is involved in sensing (hereafter simply referred to as sensor or sensor node) will perform some form of computation and get ready to send the post-processed data to the cluster head. A fundamental objective of the scheduling design is to determine the sequence of each sensor's transmission. But our framework further seeks some scheduling scheme that can strike an appropriate balance between the detection performance and the energy savings in a distributed manner. For convenience, we assume that all the sensors in a cluster are synchronized at the beginning of their transmissions. This can be achieved by having the cluster head send a beacon or synchronization message to the sensors. During the process of transmissions, however, we do not assume that these sensors are still synchronized.

We firstly identify the parameters that should be exploited in the scheduling design. As for the energy efficiency, the residual energy of each sensor i, denoted as ψ_i, which equals the sensor's current energy minus the energy required to send its data to the cluster head (i.e., e_i), serves as a good

[2]A similar capacity-like metric based on the Chernoff information was obtained in [9], but for a problem of detecting a correlated Gaussian field which is completely different from and not applicable to the radar detection problem.

measure and directly reflects each sensor node's lifetime after data transmission. D_i, as defined in (7), is another parameter we should take into account, as it indicates the importance of each sensor's data in the overall detection performance (cf. *Proposition 1*). In addition, the amplitude of a sensor's local log-likelihood ratio $|\Lambda_i|$ is one other parameter that merits our attention. In fact, as indicated in [10], $|\Lambda_i|$ reflects the extremeness or informativeness of a sensor's observation, and can be exploited to attain a reduced average number of transmissions.

Remark 2: It is worthwhile to make a remark about D_i and $|\Lambda_i|$. D_i, as defined in (7), only depends on a sensor's second-order statistics, and is noise free. It reflects the statistical tendency of a sensor's contribution to the overall detection performance in the Neyman-Pearson sense. $|\Lambda_i|$, on the other hand, contains information about a sensor's real-time observation as well as the instantaneous noise. It reflects a sensor's momentary importance to the decision making for a particular hypothesis test. $|\Lambda_i|$ is related to D_i in a statistical average sense, even monotonically. But a specific large $|\Lambda_i|$ does not necessarily suggest a large D_i, and vice versa.

Thus, in terms of the system-level performance, our design objectives are : 1) to reduce the average number of transmissions for reaching a decision; 2) to make sure the decision has a desired level of confidence. The first property is related to the log-likelihood ratio at each sensor i. The second property, if cast mathematically, can be

$$\sum_{i=1}^{N} \rho_i \, D_i > D_0,$$

where $\rho_i \in \{0, 1\}$ is an indicator variable which indicates whether sensor i elects to transmit, and D_0 is the minimum acceptable overall Kullback-Leibler distance which corresponds to a certain quantity of the detection probability given a fixed value of false alarm probability P_F. Meanwhile, considering each sensor may act selfish in order to last longer, a desirable scheduling design should extend each sensor's lifetime as well. After all, rotating the cluster head position is necessary for maintaining the clustering architecture (e.g., [3]), and the one that becomes the new cluster head is usually the one which has the largest residual energy. Hence, the manifestation of energy efficiency at the per-sensor level can be expressed as

$$\max \psi_i, \quad i = 1, \cdots, N.$$

B. A Simple Distributed Scheduling Scheme

There exist some distributed MAC or scheduling protocols (see [11] and [12] for a survey), but they are not applicable to this problem because, among other reasons, detection performance is not taken into account. Some schemes named opportunistic transmission scheduling, e.g., in [13]-[15], exploit the channel state information in random access to achieve energy efficiency. However, in this paper, the channel state information is not a major concern. To circumvent this problem, based on our previous work on the energy-performance tradeoff [2] and also inspired by the ordered transmission approach [10], we introduce a priority concept named the energy-performance index, and let sensors with higher index values to transmit earlier.

The energy-performance index for sensor i is defined to be $\delta_i = \mathcal{H}(D_i, |\Lambda_i|, \psi_i)$, where $\mathcal{H}$ is a mapping function. More specifically, $\mathcal{H}$ is a real-valued nonnegative function of D_i, $|\Lambda_i|$, ψ_i, and in general is increasing with respect to each of these parameters. $\mathcal{H}$ does not need to be a continuous function, it can be piecewise for example, and can assume different forms. For instance, if we define $h_1(\psi_i)$ as a battery cost function which is monotonic decreasing with respect to ψ_i and captures the reluctance of sensor i to transmit, then adopting the idea of detection-probability-to-energy ratio in [2], we can define the energy-performance index as

$$\delta_i = \frac{h_2(D_i, |\Lambda_i|)}{h_1(\psi_i)},$$

where $h_2(D_i, |\Lambda_i|)$ denotes a certain form of combination of D_i and $|\Lambda_i|$, and is monotonically nondecreasing with regard to either parameter. Of course, the simplest form of this $\mathcal{H}$ function is probably a linear combination of all three parameters, i.e.,

$$\delta_i = \xi_1 D_i + \xi_2 |\Lambda_i| + \xi_3 \psi_i,$$

where ξ_1, ξ_2, and ξ_3 are scaling coefficients that resemble Lagrange multipliers. In particular, when $\xi_1 = \xi_3 = 0$, this corresponds to the ordered transmission approach in [10], where sensors with more extreme observations have higher priority. If simply letting $\xi_1 = \xi_2 = 0$, it represents the conservative energy-dominating approach in which sensors with more residual energy are favored. Thus, a desired tradeoff among these parameters D_i, $|\Lambda_i|$, and ψ_i can be attained by judiciously choosing the mapping function $\mathcal{H}$, and/or tuning the coefficients for these parameters. Note that the properties of D_i, as stated in *Lemma 2*, can also be exploited to facilitate the design of $\mathcal{H}$.

We further introduce a parameter named defer time, like that in [10] and [15], to determine when each sensor transmits. Defer time is denoted by $\mathcal{J}(\delta_i)$ and is a function of each sensor's index value δ_i. It is basically the time that each sensor has to wait before transmitting their information to the cluster head. It also resembles the interframe spacing time interval[3] in IEEE 802.11 CSMA/CA protocol for which each node has to wait before transmitting even though it senses that the medium is idle. $\mathcal{J}$ should be a non-increasing function of the index value δ_i, such that sensors with higher index values will wait less time before accessing the medium. $\mathcal{J}$ can also take a variety of forms. In fact, [10] adopts a very simple form similar to $\mathcal{J}(\delta_i) = 1/\delta_i$. However, to reduce the chance of collisions, $\mathcal{J}$ should be judiciously designed along with $\mathcal{H}$, so that the resulting defer time for different sensors is well separated.

In the distributed implementation, the functions of $\mathcal{H}$ and $\mathcal{J}$ are assumed to be available at each sensor, so that each sensor can compute its index value δ_i and its defer time $\mathcal{J}(\delta_i)$ given its own local information. Each sensor can thus make an autonomous decision about when to transmit, without consultation with any of its neighbors or the cluster head. When each sensor sends, it transmits D_i and Λ_i, along with other necessary information for network maintenance.

[3]Assigning different interframe spacing to different traffic flows or users based on their priorities was considered in [16], in order to introduce service differentiation into IEEE 802.11 MAC sublayer.

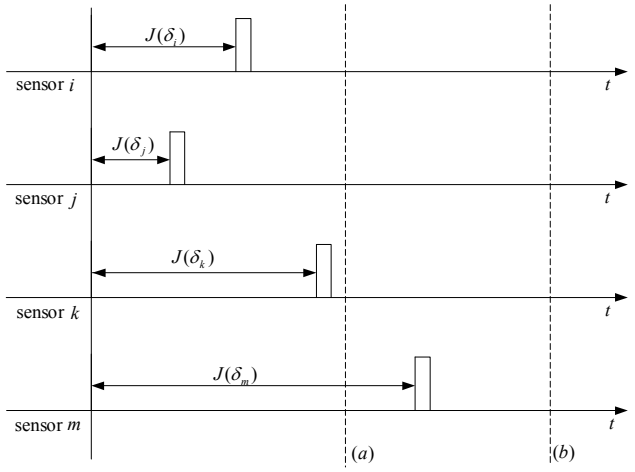


Fig. 2: Illustration of the distributed implementation. Transmissions will be stopped at point (a) when a decision can be made with a certain level of confidence, or at point (b) when the time for a single test expires.

The stopping rule should be: 1) when a decision can be made with a desired confidence level (i.e., $D > D_0$); or 2) when the time for a particular test expires. A simple example of this distributed scheduling approach is illustrated in Fig. 2. In either case, the cluster head can broadcast one beacon signal to all these sensors to stop further transmissions.

V. Distributed Routing Design

A. Problem Statement

Each cluster head will make a binary decision based on the data it retrieves from the sensors, and it will report to the fusion center, once it identifies a target at a specific range resolution cell. In addition to functioning in the event-driven mode, each cluster head also needs to periodically send status information to the fusion center for the purpose of network maintenance, and serves as a relay node for its neighboring nodes. Therefore, it appears reasonable to assume a continuous data delivery model for each cluster head. In the routing design, we are also concerned with the energy efficiency. For simplicity we consider the energy dissipated at each cluster head instead of the residual energy, although residual energy can be easily incorporated, like that in [2]. In addition, it is worth noting that routing in this scenario is quite different from that in [2], because we are dealing with multiple clusters and there could be possibly several targets appearing in different clusters at the same time. Hence, we assume each cluster head has a routing table for several possible paths that lead to the fusion center, and it can choose which path(s) to use by varying the traffic flow over that path.

Let $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ denote a finite network defined by a set $\mathcal{N}$ of nodes and a set $\mathcal{A}$ of directed arcs. In particular, we denote the fusion center as node q, thus the set of cluster head nodes is given by $\mathcal{N}\backslash q$. We denote by (i,j) the link from node i to node j. We distinguish link (i,j) from (j,i), and simply assume that if one exists the other does also. We assume the network is connected in the sense that for any two nodes i and j, there is a directed path from i and j, which is a sequence of non-repeated nodes and connecting arcs. We assume that the traffic load generated at each cluster head is moderate. Thus, flow control or congestion control schemes will not be considered in this paper.

Let $b_i \geq 0$ be the expected traffic in bits/sec generated at each cluster head i which consists of information-bearing data and status information. We define $b_q = 0$. For link (i,j), let e_{ij} be the energy consumption corresponding to sending one unit traffic (per bit/sec) over it, and C_{ij} be the transmission capacity[4] of link (i,j). Thus, the routing objective is to divide the traffic among the paths from each cluster head to the fusion center in a way that the resulting total link flow patterns minimizes the energy consumption. The routing problem can be then formulated as follows:

$$\begin{aligned} \text{P.1}: \quad \min \quad & \sum_{(i,j)} e_{ij} \cdot F_{ij} \\ \text{s.t.} \quad & \sum_{\{j:(i,j)\in\mathcal{A}\}} F_{ij} - \sum_{\{j:(j,i)\in\mathcal{A}\}} F_{ji} = b_i \\ & 0 \leq F_{ij} < C_{ij}, \quad \forall (i,j) \in \mathcal{A} \\ & F_{qi} = 0, \quad \forall i \in \mathcal{N}\backslash q \end{aligned}$$

where F_{ij} denotes the amount of flow over link (i,j) and is the decision variable.

P.1 is a multicommodity flow problem, and can be solved relatively easily in a centralized manner with some linear programming techniques. However, in general, it is nontrivial to solve P.1 directly in a distributed manner[5]. As a result, we start by modifying P.1 into a slightly different formulation which can be more amenable to distributed computation. Our first task is to eliminate the link capacity constraint $F_{ij} < C_{ij}$. One approach to achieve this is to apply the *penalty function method*. We hereby introduce a new cost function U_{ij} which has the following properties:

1) U_{ij} is a real-valued function only of F_{ij} and is defined on an interval $[0, C_{ij})$.
2) U_{ij} is nonnegative continuous increasing with respect to F_{ij}, and has continuous first and second derivatives.
3) U_{ij} is strictly convex.
4) U_{ij} grows at an infinite rate as F_{ij} approaches the boundaries of the domain of U_{ij}, i.e., $U_{ij}(F_{ij}) \to \infty$ as $F_{ij} \to C_{ij}$.

A possible choice of the cost function U_{ij} could be, for example,

$$U_{ij}(F_{ij}) = e_{ij} \cdot F_{ij} + \frac{\alpha}{C_{ij} - F_{ij}}, \tag{9}$$

where α is a positive scaling parameter. Applying this new cost function U_{ij}, P.1 becomes a convex cost network flow problem without arc flow bounds, which hereby is denoted as problem P.2, but for brevity is not explicitly given here. It can be verified that if Problem P.2 has at least one feasible solution, it will have a unique optimal solution [6].

Our next task is to define a new set of decision variables

[4]The capacity of a wireless link is interrelated with other wireless links in the neighborhood, and is a function of transmitter powers (its own and nodes in the vicinity) and the channel conditions.

[5]There exist some works which attempt to solve this type of problem in a distributed way (e.g., [17]), but they either do not meet our design need, or are not amenable to implementation.

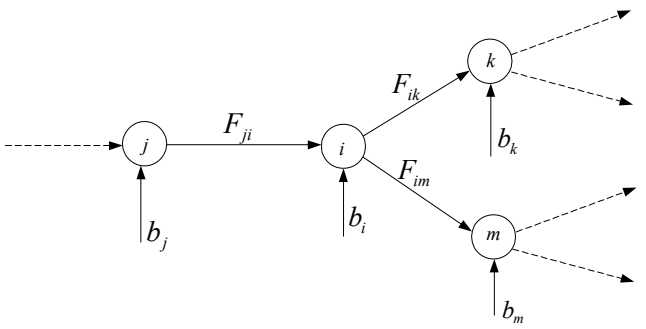


Fig. 3: A simple example of several connected cluster heads whereby for node i, we have $a_i = b_i + F_{ji}$, $\rho_{ik} = F_{ik}/a_i$, $\rho_{im} = F_{im}/a_i$.

that are suitable for distributed iterative computation. Let a_i be the total traffic or simply the node flow at cluster head i. a_i includes both b_i and the traffic from other cluster heads that traverses through i, i.e.,

$$a_i = b_i + \sum_{\{j:(j,i)\in\mathcal{A}\}} F_{ji}, \quad i \in \mathcal{N}\backslash q. \tag{10}$$

Eq. (10) also implicitly states the conservation of flow at each cluster head, i.e., the expected traffic into a cluster head is equal to the expected traffic out of it. For $a_i \neq 0$, we let $0 \leq \rho_{ij} \leq 1$ be the fraction of the node flow a_i that is routed over link (i,j), i.e.,

$$\rho_{ij} = \frac{F_{ij}}{a_i}, \quad i \in \mathcal{N}\backslash q, (i,j) \in \mathcal{A}. \tag{11}$$

We take $\rho_{qj} = 0$ for any $j \in \mathcal{N}\backslash q$ and $(q,j) \in \mathcal{A}$ such that traffic which has reached the fusion center is not sent back into the network. It is obvious that

$$\sum_{\{j:(i,j)\in\mathcal{A}\}} \rho_{ij} = 1, \quad \forall i \in \mathcal{N}\backslash q, \tag{12}$$

which is another way to describe the conservation of flow. Fig. 3 provides a simple example to illustrate these parameters. Further, we say there exists a routing path for a cluster head node $i \in \mathcal{N}\backslash q$ to the fusion center q, if there is a sequence of nodes, $i, j, \cdots, k, q$ such that $\rho_{ij} > 0, \cdots, \rho_{kq} > 0$.

Let $\boldsymbol{\rho}$ be a column vector which contains all the elements (in some order) of the set $\{\rho_{ij}, (i,j) \in \mathcal{A}, i \neq q\}$. Let $\mathbf{a}$ be the node flow vector containing a_i for each $i \in \mathcal{N}\backslash q$, $\mathbf{b}$ be the input traffic vector with elements b_i for each $i \in \mathcal{N}\backslash q$, and $\mathbf{F}$ be the vector of F_{ij}, $\forall (i,j) \in \mathcal{A}$. We also define a set

$$\boldsymbol{\Omega} = \left\{ \boldsymbol{\rho} \left| \rho_{ij} \geq 0, \sum_{\{j:(i,j)\in\mathcal{A}\}} \rho_{ij} = 1, \forall (i,j) \in \mathcal{A}, \forall i \in \mathcal{N}\backslash q \right. \right\}$$

Let $\bar{\boldsymbol{\Omega}}$ be a subset of $\boldsymbol{\Omega}$ consisting of all $\boldsymbol{\rho}$ for which there exists a routing path for every cluster head node $i \in \mathcal{N}\backslash q$ to the fusion center. It can be verified that for each $\boldsymbol{\rho} \in \bar{\boldsymbol{\Omega}}$ and $\mathbf{b}$ with $b_i \geq 0$, the set of equations (10) and (11) has unique solutions for $\mathbf{a}$ and $\mathbf{F}$, whose components can be written as functions of $\mathbf{b}$ and $\boldsymbol{\rho}$, i.e., $a_i(\boldsymbol{\rho}, \mathbf{b})$ and $F_{ij}(\boldsymbol{\rho}, \mathbf{b})$, respectively. On the other hand, for every $\mathbf{b}$ with $b_{ij} \geq 0$ and every $\mathbf{F}$ which is feasible for P.2, there exists a $\boldsymbol{\rho} \in \bar{\boldsymbol{\Omega}}$ which, when plugged into the function $F_{ij}(\boldsymbol{\rho}, \mathbf{b})$, will produce $\mathbf{F}$. Thus, for each input set $\mathbf{b}$, there exists a unique mapping between the two sets of routing variables, $\mathbf{F}$ and $\boldsymbol{\rho}$. Such unique mapping enables us to reformulate P.2 in terms of the new set of routing variables $\boldsymbol{\rho}$, and the resulting new formulation is given by

$$\text{P.3}: \quad \min \quad U(\boldsymbol{\rho}, \mathbf{b}) \triangleq \sum_{(i,j)} U_{ij}[F_{ij}(\boldsymbol{\rho}, \mathbf{b})]$$
$$\text{s.t.} \quad \boldsymbol{\rho} \in \bar{\boldsymbol{\Omega}}.$$

Algorithm 1 Information exchange at each cluster head i

1: Receive the value of $\partial U/\partial b_k$ from each of its downstream neighbors $j \neq q$ ($\rho_{ij} > 0$).
2: If any downstream neighbor also sends a special blocking tag, put that neighbor node in a set $\mathcal{B}(i)$.
3: Calculate the value $\partial U/\partial b_i$ from

$$\frac{\partial U}{\partial b_i} = \sum_{\{j:(i,j)\in\mathcal{A}\}} \rho_{ij} \left(U_{ij}^{'} + \frac{\partial U}{\partial b_j} \right), \quad i \in \mathcal{N}\backslash q.$$

4: For each downstream neighbor $j \neq q$, determine if the following conditions are satisfied:

$$\rho_{ij} > 0 \text{ and } \frac{\partial U}{\partial b_i} \leq \frac{\partial U}{\partial b_j};$$
$$\rho_{ij} \geq \frac{\varpi}{a_i} \left[U_{ij}^{'} + \frac{\partial U}{\partial b_j} - \frac{\partial U}{\partial b_i} \right],$$

where ϖ is a scale factor. If the above conditions are satisfied, add k into the set $\mathcal{B}(i)$.
5: Broadcast $\partial U/\partial b_i$ to the upstream neighbors. If $|\mathcal{B}(i)| \neq 0$, also send a blocking tag.

Algorithm 2 Variable update at each cluster head i

1: **for all** $j \in \{j : (i,j) \in \mathcal{A}\}$ **do**
2: **if** $j \in \mathcal{B}(i)$ **then**
3: $\rho_{ij} \leftarrow 0$, and $\Delta_{ij} \leftarrow 0$.
4: **else**
5: Compute

$$z_{ij} = \left(U_{ij}^{'} + \frac{\partial U}{\partial b_j} \right) - \min_{\{k:(i,k)\in\mathcal{A}, k\notin\mathcal{B}(i)\}} \left(U_{ik}^{'} + \frac{\partial U}{\partial b_k} \right),$$

and let k_{min} be a value of k which achieves the minimization in the above equation.
6: Compute

$$\Delta_{ij} = \min \left(\rho_{ij}, \frac{\varpi \cdot z_{ij}}{a_i} \right).$$

7: Update the routing variable ρ_{ik}:

$$\rho_{ij} \leftarrow \begin{cases} \rho_{ij} - \Delta_{ij}, & j \neq k_{min} \\ \rho_{ij} + \sum\limits_{j \neq k_{min}} \Delta_{ij}, & j = k_{min} \end{cases}$$

8: **end if**
9: **end for**

B. A Simple Distributed Routing Algorithm

There are several algorithms that can be used to solve P.3, which allow each cluster head i to determine its own routing variables ρ_{ij}. Among them are [18]-[20]. As the algorithm given in [18] requires only the first-order derivative of the objective function and demands less computational effort, we choose to adapt such algorithm to solve P.3 in a distributed fashion. The final routing algorithm is composed of two parts:

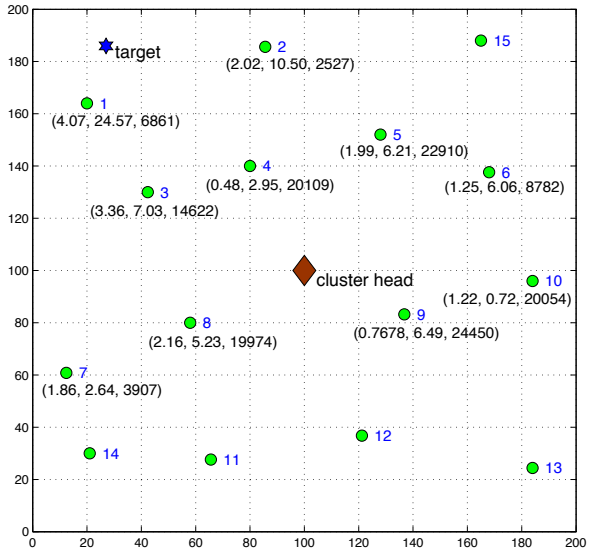


Fig. 4: A snapshot for a particular cluster, where each sensor that participates in sensing is annotated with a 3-tuple $(D_i, |\Lambda_i|, \psi_i)$.

1) a protocol for information exchange between neighboring cluster heads, as summarized in Algorithm 1; 2) a method for updating the routing variables at each cluster head, as shown by Algorithm 2. In both Algorithm 1 and 2, we use $U_{ij}^{'}$ for $\partial U_{ij}/\partial(F_{ij})$ for short[6]. In Algorithm 1, we also distinguish between a cluster head's neighbors. We say cluster head j is downstream from cluster head i if there is a directed path from i to j, and for every link (k, m) on the path, we have $\rho_{km} > 0$. We say cluster head i is upstream from cluster head j if j is downstream from i. Further, if there is no pair of cluster heads i, j such that i is both upstream and downstream from node j, we say the routing is loop free.

This distributed routing algorithm can be implemented independently at each cluster head i. It successively updates the routing variables ρ_{ij} based on information communicated in an orderly fashion from neighboring cluster heads. The optimality and the convergence of this algorithm are both ensured, as proved originally in [18]. Further, it has a property of being loop free at every iteration, which can prevent the potential deadlock in Algorithm 1 during the information exchange between neighboring cluster heads. When initializing this algorithm, it is also desirable to start with a loop free $\boldsymbol{\rho} \in \bar{\boldsymbol{\Omega}}$., for example, the min-hop path or the greedy path. After initialization, each cluster head will run the algorithm locally for multiple iterations until the total energy cost converges. Since this routing algorithm is implemented in a distributed fashion, it can react rapidly to a local disturbance and result in a slower fine tuning in the rest of the network. It is thus also applicable when the input statistics are slowly changing with time.

[6]Note that each cluster head can estimate, as a time average, the traffic F_{ij} for each outgoing link, and the estimated F_{ij} can be used to calculate $U_{ij}^{'}$.

TABLE I: Transmission Sequence

Type	Description	Sequence	$\sum \rho_i$
1	ordered ψ_i	$9, 5, 4, 10, 8, 3, 6, 1$	8
2	ordered $\|\Lambda_i\|$	$1, 2, 3$	3
3	ordered D_i	$1, 3, 8, 2$	4
4	$\mathcal{H}_1(D_i, \|\Lambda_i\|, \psi_i)$	$1, 5, 9, 3$	4
5	$\mathcal{H}_2(D_i, \|\Lambda_i\|, \psi_i)$	1, 3, 5, 8	4

VI. Simulation Results

In this section, we present some simulation results to illustrate this distributed framework. We firstly demonstrate the advantages of the proposed distributed scheduling approach. Consider a cluster as shown in Fig. 4, where 15 sensors are randomly distributed in a $200m \times 200m$ region, and the cluster head is located at (100, 100). We assume $N = 10$ sensors are chosen to probe a range resolution cell that contains a target. To reflect the difference in each sensor's battery level, we designate a uniformly distributed random number in the interval of $[2000, 25000]$ (in μJ) as each sensor's current energy. When computing D_i and Λ_i for each sensor, we consider both the sensor-target distance and the scattering effect. For this target-present case, we assume $\Lambda_i \geq 0$ for simplicity. To estimate the consumed energy for data transmission from each sensor to the cluster head, we adopt a simple path loss model. We assign a 3-tuple $(D_i, |\Lambda_i|, \psi_i)$ to each of the N sensors, as shown in Fig. 4. This scenario represents a snapshot of this particular cluster.

In this example, we consider five distributed scheduling approaches, which are the following:

1) Ordered ψ_i: a pure energy based approach which schedules sensors with larger ψ_i for earlier transmissions;
2) Ordered $|\Lambda_i|$: this is the approach proposed in [10], which favors sensors with more extreme observations;
3) Ordered D_i: this approach gives higher priority to sensors with larger contributions to the detection performance;
4) $\mathcal{H}_1(D_i, |\Lambda_i|, \psi_i)$: our proposed approach that jointly considers $D_i, |\Lambda_i|$, and ψ_i. $\mathcal{H}_1$ is defined as:
$$\mathcal{H}_1(D_i, |\Lambda_i|, \psi_i) = 2D_i + |\Lambda_i| + \psi_i/1500;$$
5) $\mathcal{H}_2(D_i, |\Lambda_i|, \psi_i)$: $\mathcal{H}_2$ is a nonlinear function, and is defined as
$$\mathcal{H}_2(D_i, |\Lambda_i|, \psi_i) = 2D_i + |\Lambda_i| - 10^5/\psi_i.$$

Note that the nonlinear part $10^5/\psi_i$ in $\mathcal{H}_2$ can be regarded as a measure of the reluctance of sensor i in transmitting. For Approach 1-3, we assume the same stopping rule, i.e., $\sum \rho_i \Lambda_i > \eta$, where η is the test threshold and is set as 40 for this example. For Approach 4-5, the stopping rule is $\sum \rho_i \Lambda_i > \eta$ and $\sum \rho_i D_i > D_0$, where D_0 is chosen as 10.

In Table I, we list the resulting transmission sequences under these approaches. In Fig. 5, we further compare the performance of these approaches, in terms of the overall Kullback-Leibler distance ($\sum \rho_i D_i$), the accumulated log-likelihood ratios ($\sum \rho_i \Lambda_i$), the minimum residual energy

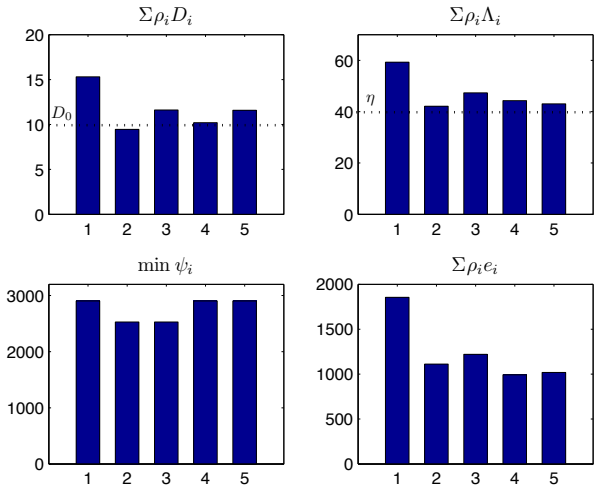


Fig. 5: Comparison of the scheduling approaches in terms of $\sum \rho_i D_i$, $\sum \rho_i \Lambda_i$, $\min \psi_i$, and $\sum \rho_i e_i$.

$(\min \psi_i)$, and the total energy consumption $(\sum \rho_i e_i)$. It is observed that Approach 1 achieves the largest value of $\min \psi_i$, as it protects sensors with smaller ψ_i by not scheduling them to transmit. However, without considering the detection performance at all, Approach 1 results in a dramatic increase in both the amount of consumed energy and the number of transmissions. Approach 2 has the least number of transmissions. But without considering D_i, it does not achieve the desired detection performance in this specific example (i.e., $\sum \rho_i D_i < 10$). It may also result in draining out a certain sensor earlier (i.e., small value of $\min \psi_i$). Approach 3 satisfies the detection performance requirement in terms of $\sum \rho_i D_i > 10$. But without considering energy, this approach has mediocre performance in both $\min \psi_i$ and $\sum \rho_i e_i$. Approach 4 and 5, although dictated by different $\mathcal{H}$ functions, both achieve better performance-energy balances than the other schemes. Their weighted combinations allow a decision to be made within a moderate number of transmissions and with the desired level of confidence. Furthermore, they also successfully avoid burdening nodes with small residual energy, and achieve the minimal amount of total energy consumption.

Next, we illustrate the performance of the distributed routing algorithm through simulating a simple example. We assume 9 cluster heads and a fusion center (labeled as q) are distributed over a field of $1600m \times 1600m$, and we set the transmit range of each cluster head to $500m$. The topology is shown in Fig. 6. To estimate e_{ij}, we compute the distance between each pair of linked cluster heads, and apply a simple path loss model where the path loss exponent is set to 2. We assume that for each link in Fig. 6, c_{ij} is known and fixed, and we adopt Eq. (9) for the cost function $U_{ij}(F_{ij})$ where α is set to 0.1. The unit for the total cost $\sum U_{ij}(F_{ij})$ can be deemed to be nJ/s, although $U_{ij}(F_{ij})$ in (9) also includes a penalty part.

We choose $\varpi = 2$ for the scale parameter in Algorithm 1 and 2, and simply adopt the greedy path to initialize the distributed routing algorithm. We generate different sets of input traffic $\mathbf{b}$, given that b_i (bits) is a uniform random number

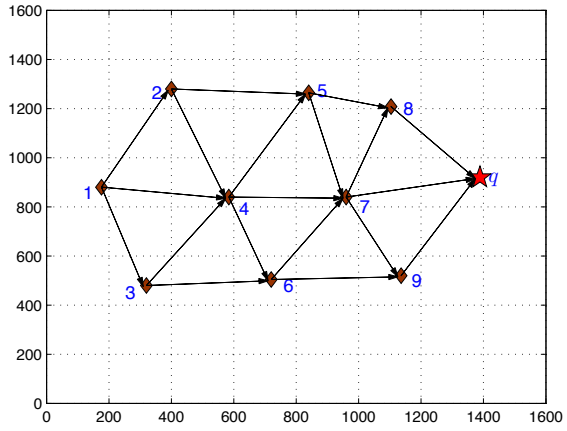


Fig. 6: Network topology used for the simulation example.

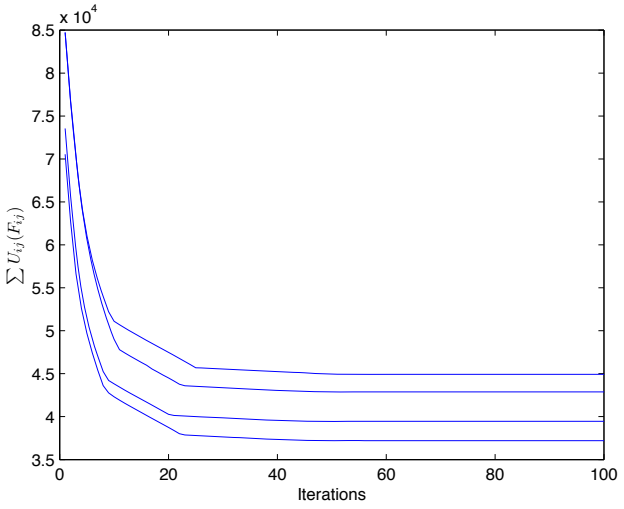


Fig. 7: Convergence of the total cost $\sum U_{ij}(F_{ij})$ given different sets of input traffic $\mathbf{b}$.

over the interval $[100, 200]$. For each set of input traffic, we run the distributed routing algorithm at each cluster head for multiple iterations. For each iteration, we calculate and record the resulting total cost $\sum U_{ij}(F_{ij})$. We plot the value of $\sum U_{ij}(F_{ij})$ versus the iteration number for 4 different sets of $\mathbf{b}$ in Fig. 7. It is clearly seen that the value of the energy cost function converges smoothly to the optimal value, and the convergence takes roughly 25 iterations.

VII. Conclusion

In this paper, we proposed a distributed and energy-efficient framework for the problem of Neyman-Pearson detection of fluctuating radar signals in large-scale sensor networks. Our framework is scalable with respect to the network size, and can greatly alleviate the requirement on the storage and processing capability of the fusion center. It adopts a clustering architecture, and includes a distributed scheduling protocol and a distributed routing protocol to handle information transmissions at intra-cluster and inter-cluster levels, respectively. The distributed scheduling protocol allows each

sensor inside a cluster to make an autonomous decision about when to send data to the cluster head, according to its own information and without consulting any other sensors. The distributed routing protocol enables each cluster head to make its own routing decisions, with its available information and information obtained from consultation with immediate neighbors. Simulation examples demonstrate the superior tradeoff attained by the distributed scheduling approach between the detection performance and the energy efficiency, and the fast convergence of the distributed routing algorithm to the optimal value of the total energy cost.

REFERENCES

[1] Y. Yang and R. S. Blum, "Energy-efficient routing for signal detection under the Neyman-Pearson criterion in wireless sensor networks," in *Proc. IPSN*, pp. 303-312, Cambridge, MA, April 2007.

[2] Y. Yang, R. S. Blum, and B. M. Sadler, "Energy-efficient routing for signal detection in wireless sensor networks," *IEEE Trans. Signal Process.*, vol. 57, no. 6, pp. 2050-2063, June 2009.

[3] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An application-specific protocl architecture for wireless microsensor networks," *IEEE Trans. Wireless Commun.*, vol. 1, pp. 660-670, October 2002.

[4] M. I. Skolnik, Ed., *Radar Handbook*, McGraw-Hill, New York, 2nd Edition, 1990.

[5] H. L. Van Trees, *Detection, Estimation, and Modulation Theory, Part I*, Wiley, New York, 1968.

[6] Y. Yang, *Signal Processing and Communications for Radar Sensor Networks*, Ph.D. dissertation, Lehigh University, 2009.

[7] S. Kullback, *Information Theory and Statistics*, John Wiley & Sons,, New York, 1959.

[8] J. A. Bucklew, *Large Deviation Techniques in Decision, Simulation, and Estimation*, John Wiley & Sons,, New York, 1990.

[9] Y. Sung, S. Misra, L. Tong, and A. Ephremides, "Cooperative routing for distributed detection in large sensor networks," *IEEE J. Sel. Areas Commun.*, vol. 25, pp. 471-483, February 2007.

[10] R. S. Blum and B. M. Sadler, "Energy efficient signal detection in sensor networks using ordered transmissions," *IEEE Trans. Signal Process.*, vol. 56, pp. 3229-3234, July 2008.

[11] I. Demirkol, C. Ersoy, and F. Alagöz, "MAC protocols for wireless sensor networks: a survey," *IEEE Commun. Mag.*, pp. 115-121, April 2006.

[12] S. Jain and S. Srivastava, "A survey and classification of distributed scheduling algorithms for sensor networks," in *Proc. SENSORCOMM*, pp. 88-93, 2007.

[13] X. Liu, E.K.P. Chong, and N. B. Shroff, "Opportunistic transmission scheduling with resource-sharing constraints in wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 19, pp. 2053-2064, October 2001.

[14] X. Qin, and R. Berry, "Exploiting multiuser diversity for medium access control in wireless networks," in *Proc. IEEE INFOCOM*, pp. 1084-1094, San Francisco, CA, 2003.

[15] Q. Zhao and L. Tong, "Opportunistic carrier sensing for energy-efficient information retrieval in sensor networks," *EURASIP J. Wireless Communications and Networking*, pp. 231-241, April 2005.

[16] I. Aad and C. Castelluccia, "Differentiation mechanism for IEEE 802.11," in *Proc. IEEE INFOCOM*, pp. 209-218, Anchorage, Alaska, April 2001.

[17] B. Awerbuch, R. Khandekar, and S. Rao, "Distributed algorithms for multicommodity flow problems via approximate steepest descent framework," in *Proc. the ACM-SIAM Symposium on Discrete Algorithms*, pp. 949-957, New Orleans, Louisiana, 2007.

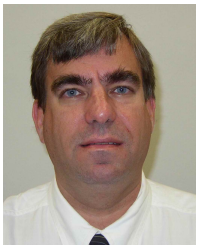
[18] R. G. Gallager, "A mininum delay routing algorithm using distributed computation," *IEEE Trans. Commun.*, vol. COM-25, pp. 73-85, January 1977.

[19] D. P. Bertsekas, E. M. Gafni, and R. G. Gallager, "Second derivative algorithms for minimum delay distributed routing in networks," *IEEE Trans. Commun.*, vol. COM-32, pp. 911-919, August 1984.

[20] S. Vutukury and J. J. Garcia-Luna-Aceves, "A simple approximation to minimum-delay routing," in *Proc. ACM SIGCOMM*, pp. 227-238, September 1999.

Yang Yang (M'10) received the B.Eng. degree in information engineering from Xi'an Jiaotong University, Xi'an, China, in 2001, the M.Eng. degree in electrical engineering from the National University of Singapore in 2004, and the Ph.D. degree in electrical engineering from Lehigh University, Bethlehem, PA, in 2009.

From 2002 to 2004, he was with the Institute for Infocomm Research, Singapore, as a Research Student. During the summer of 2007, he was an intern at Bell Laboratories, Alcatel-Lucent, Crawford Hill, Holmdel, NJ. He is currently a Postdoctoral Research Associate at Lehigh University. His research interests include communications, signal processing, and their applications to distributed sensor processing and wireless sensor networks.



Rick S. Blum received a B.S. in Electrical Engineering from the Pennsylvania State University in 1984 and his M.S. and Ph.D in Electrical Engineering from the University of Pennsylvania in 1987 and 1991.

From 1984 to 1991 he was a member of technical staff at General Electric Aerospace in Valley Forge, Pennsylvania and he graduated from GE's Advanced Course in Engineering. Since 1991, he has been with the Electrical and Computer Engineering Department at Lehigh University in Bethlehem, Pennsylvania where he is currently a Professor and holds the Robert W. Wieseman Chaired Professorship in Electrical Engineering. His research interests include communications, sensor networking, sensor processing and related topics in the areas of signal processing and communications. He is currently an associate editor for the IEEE Communications Letters and he is on editorial board for the Journal of Advances in Information Fusion of the International Society of Information Fusion. He was an associate editor for IEEE Transactions on Signal Processing and edited special issues for this journal and for JSAC. He was a member of the Signal Processing for Communications Technical Committee of the IEEE Signal Processing Society and is a member of the Communications Theory Technical Committee of the IEEE Communication Society. He is also on the awards Committee of the IEEE Communication Society.

Dr. Blum is a Fellow of the IEEE, an IEEE Third Millennium Medal winner, a member of Eta Kappa Nu and Sigma Xi, and holds several patents. He was awarded an ONR Young Investigator Award in 1997 and an NSF Research Initiation Award in 1992. His IEEE Fellow Citation "for scientific contributions to detection, data fusion and signal processing with multiple sensors" acknowledges some early contributions to the field of sensor networking.

Brian M. Sadler (Fellow, IEEE; Fellow, Army Research Laboratory) received the B.S. and M.S. degrees from the University of Maryland, College Park, and the PhD degree from the University of Virginia, Charlottesville, all in electrical engineering.

He is a senior research engineer at the Army Research Laboratory (ARL) in Adelphi, MD. Dr. Sadler is an associate editor for EURASIP Signal Processing, was an associate editor for the IEEE Transactions on Signal Processing and IEEE Signal Processing Letters, and has been a guest editor for several journals including IEEE JSTSP, IEEE JSAC, and the IEEE SP Magazine. He is a member of the IEEE Signal Processing Society Sensor Array and Multi-channel Technical Committee, and has been active in IEEE conference planning and organization for many years. He received a Best Paper Award (with R. Kozick) from the Signal Processing Society in 2006. He has received several ARL and Army R&D awards, as well as a 2008 Outstanding Invention of the Year Award from the University of Maryland (with J. Baras and P. Yu). His research interests include information science, networked and autonomous systems, acoustics, optics, and mixed-signal integrated circuit architectures. He has co-authored more than 275 publications and several patents in these areas.